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Optimal Selection Of Machining Parameters In CNC Turning Process Of EN-31 Using Intelligent Hybrid Decision Making Tools

G.Harinath Gowd[a]*, M. Venugopal Goud [b], K. Divya Theja [c], M. Gunasekhar Reddy[d]

[a]professor, [c,d]Assistant Professor, Dept. of ME, Madanapalle Institute of Technology & Science, Madanapalle, A.P., INDIA.
[b]Associate Professor, G Pullreddy Engineering College, Kurnool, A.P., INDIA

Abstract

Nowadays numerical and Artificial Neural Networks (ANN) methods are widely used for both modeling and optimizing the performance of the manufacturing technologies. Optimum machining parameters are of great concern in manufacturing environments, where economy of machining operation plays a key role in competitiveness in the market. Therefore the present research is aimed at finding the optimal process parameters for turning process of EN-31. EN-31 is chosen as the work material because of its wide applicability as material for Ball and roller bearings, spinning tools, Beading rolls, Punches and dies and by its character it has very high resistance nature against wear and can be used for components subjected to severe abrasion, wear or high surface loading. Turning is used to produce rotational, typically axi-symmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Turning is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that turning can offer, it is ideal for adding precision rotational features to a part whose basic shape has already been formed. Keeping in view of the importance of turning process, it is very important to automate the process. In order to automate the system or process it is essential to find the optimal process parameters. Hence intelligent hybrid decision making tools are applied to find the optimal process parameters. First the experiments were conducted as per the design of experiments, and then ANN is applied to predict the models for the chosen output responses. Later the models after testing for its adequacy using ANOVA Analysis, they may be chosen for subsequent optimization of the process parameters using Evolutionary techniques. The obtained optimal process parameters will be used to automate the process

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* Corresponding author. Tel.: +91-9441190044;
E-mail address: harinathgowdg@mits.ac.in

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1. Introduction

Machining involves the shaping of a part through removal of material. A tool, constructed of a material harder than the part being formed, is forced against the part, causing material to be cut from it. Machining, also referred to as cutting, metal cutting, or material removal, is the dominant manufacturing shaping process. It is both a primary as well as a secondary shaping process. The device that does the cutting or material removal is known as the machine tool. Nearly all castings and products formed by deformation processing [bulk or sheet metal] require some machining to obtain the desired final shape or surface characteristics. The material is generally removed in the form of chips. The primary reasons for selecting machining over the other two primary shaping processes are Improved surface finish and dimensional tolerances, Produce complex geometries in low quantities economically because of more flexibility in tooling, fixturing, low operating costs and lower setup times [time to prepare tooling for production]. In many cases, machining is a secondary operation for casting and forming processes, to obtain the required dimensional tolerances, surface finish, or complex geometry of the part. Machining is the only primary forming process that is also used for secondary operations. This unique characteristic has led to the dominance of this process. There are several different classifications of machining processes. One classification is by the type of cutting tools; a second is by the type of surface generated. The classification by the type of surface generated is more important, because the surface of the product is one of the major criteria considered in the selection of the manufacturing process. The classification based on the type of cutting tool considers the number of cutting edges of the tool. They are 1. *Single-point cutting:* processes such as turning, planning, shaping and boring & *2. Multiple-point cutting* (Two edges: drilling, *n* edges: milling, sawing, reaming, broaching, etc, Infinite number of edges: grinding, polishing).

1.1. Machining Variables and Relationships

There is a wide variety of machining processes, which leads to numerous variables and relationships. The key variables related to most of the machining processes are cutting speed or velocity [V], ft/min or in/sec, feed *[f],* in/rev or mm/rev and depth of cut *[d],* in. or mm. These three variables have a major effect upon the material [or metal] removal rate [MRR], which has a major role in determining the power requirements. In addition, these parameters also have a major effect upon the economics of the processes.

1.2. Main Variables that affect the Chip Formation

The three main variables that affect the formation of the chips in cutting are the tool geometry, work and tool materials. The interaction between the tool and work material is also significant: this is often mentioned as the fourth main variable. The tool geometry is described by the various angles and nose radius of the single-point tool illustrated in figure 1.

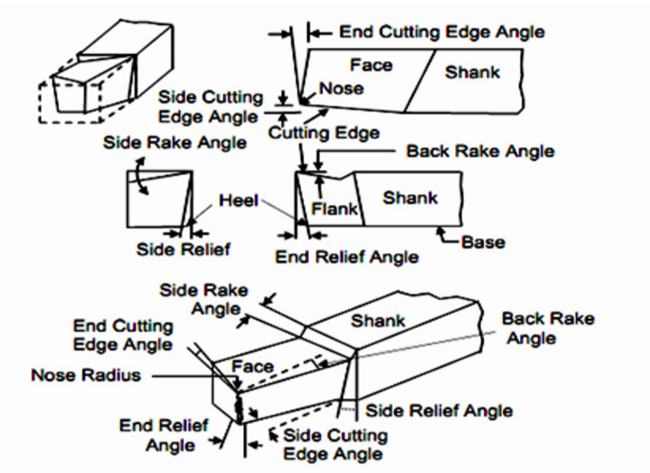

Figure 1. Tool geometry

The tool wear occurs on the flank face [flank wear] or on the top face [crater wear]. The types of chips formed are generally classified into three types. They are *Discontinuous [segmented] chips:* from hard, brittle materials and from two-phase materials that separate easily, such as leaded steels and gray cast irons. *Continuous chips:* sharp, long, continuous chips, which can be sharp and hot and thus dangerous, steel and aluminium. *Built-up edge:* part of the chip adheres to the tool, which produces rough surfaces on the finished part.

The figure 2 is a schematic representation of the chip formation process as sketched with the help of a photograph of chip initiation [right]. In this representation, we can see a continuous plastic deformation that can be subdivided into four zones. The transition from the work piece structure [a] to the chip structure [b] is made by simple shearing [shear zone]. When cutting brittle materials, minor deformation on the shear plane can already lead to material detachment. If however the material has higher deformability, detachment first occurs in front of the cutting edge in zone [e]. The tensile load under simultaneous perpendicularly active pressure leads, together with the high temperatures prevalent here, to strong deformations on the peripheries of the rake face [c] and cut surface [d]. Sliding over the tool surfaces causes further plastic deformations to arise in the boundary layers. The “flow zone” [the non-etched white zone on the bottom of the chip], the deformation texture of which forms parallel to the rake face, gives the impression of a viscous flow process with an extremely high degree of deformation. The chip resulting from the described chip formation process is designated as a continuous chip. Other chip types include lamellar chips, segmented chips and discontinuous chips.

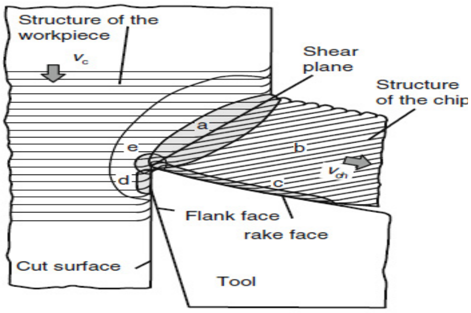

Figure 2. Chip formation

1.3. Tool Wear

During the machining process, the cutting tools are loaded with the heavy forces resulting from the deformation process in chip formation and friction between the tool and work piece. The heat generated at the deformation and friction zones overheats the tool, the chip and partially the work piece. All the contact surfaces are usually clean and chemically very active; therefore the cutting process is connected with complex physical-chemical processes. Wear on the tool, which occurs as the consequence of such processes, is reflected as progressive wearing of particles from the tool surface.

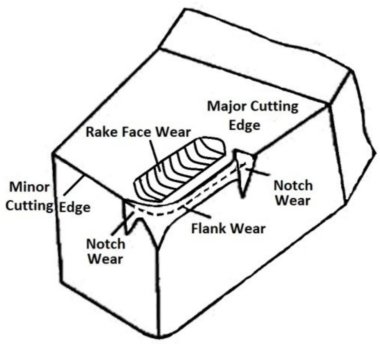

Figure 3. Tool wear phenomenon

Cutting tools are subjected to an extremely severe rubbing process. They are in metal-to metal contact between the chip and work piece, under conditions of very high stress at high temperature. The situation is further aggravated [worsened] due to the existence of extreme stress and temperature gradients near the surface of the tool. During machining, cutting tools remove material from the component to achieve the required shape, dimension and surface roughness [finish]. However, wear occurs during the cutting action, and it will ultimately result in the failure of the cutting tool. When the tool wear reaches a certain extent, the tool or active edge has to be replaced to guarantee the desired cutting action. The following are the consequences of tool wear 1. Increase the cutting force; 2. Increase the surface roughness; 3. Decrease the dimensional accuracy; 4. Increase the temperature; 5. Vibration; 6. Lower the production efficiency, component quality; 7. Increase the cost.

1.4. Cutting Tool Materials

Tool change times, and with them both manufacturing times and tool, machine and labour costs, are affected by wear. Wear is affected in turn by the properties of the cutting tool materials. Development in the cutting tool material sector is therefore far from finished, but is constantly aiming both to improve cutting tool materials that are already established as well as to discover new materials for use in the manufacture of cutting tools. Cutting tool materials should have the following properties (hardness and pressure resistance, bending strength and toughness, edge strength, inner bonding strength, high temperature strength, oxidation resistance, small propensity to diffusion and adhesion, abrasion resistance, reproducible wear behaviour) in order to do justice to the stresses placed on them. The general cutting tool materials used are Tool steels, Cemented carbides, Ceramics, Super-hard cutting tool materials made of boron nitride and diamond.

With the advent of CNC technology, the machining processes are automated through which high quality of the machined components; high material removal rates can be achieved. In general, CNC lathe machine is operated with several controllable factors such as spindle speed, feed rate, depth of cut etc. In this work, metal removal rate and tool wear are considered as the performance measures as they affect cost and quality of the finished components. The optimization of CNC turning process is often achieved by trial-and-error method based on the shop floor experiences by determining the certain parameters of the process. But this does neither guarantee the quality nor the machining economics. Therefore a general optimization plan is required to avoid cumbersome trial runs on machine and wastages. Optimization of CNC Turning has been carried out in the literature by many researchers. A few works are based on simulations [1-4] and other works are based on many experimental runs [5-6], collecting huge amount of data and processing it to achieve the result. Taguchi method is widely adopted in the literature for the improvement of quality and machining economics. Taguchi method uses the orthogonal array concept with small number of experimental runs to investigate the effects of parameters on performance measures reduces the sensitivity due to inherent variations present in the system. Moreover, Taguchi method does not consider the interactive effects of control factors. Machining is the only primary forming process that is also used for secondary operations. This unique characteristic has led to the dominance of this process. Due to the high cost of machining and problems caused by the chips produced, casting and deformation processing try to produce “near-net shape” products, which can be completed with little or no machining. So In the present work, CNC Turning process is investigated by considering the performance measures, metal removal rate (MRR) and tool wear (TW) in terms of spindle speed, feed rate and depth of cut as control factors.

2. Experimental work

The experiments were conducted on a high precision All geared Lathe. The following are the specifications of the lathe. This table will give the ranges of the speed, feed, and depth of cut of the lathe machine that are possible to set are the Swing over the bed=310mm, Length of bed=1530mm and Number of speeds=18. EN31 is used as the work material because by its character it has very high resistance nature against wear and can be used for components subjected to severe abrasion, wear or high surface loading and widely used in Ball and roller bearings, spinning tools, Beading rolls, Punches and dies. The property of EN 31 is same as that of E52100 of SAE grade. It contains 0.5-1.1% of carbon, 1.3 -1.5% of chromium. It has very good physical properties like it is very lustrous (shiny), good conductors of heat and electricity, high melting point –high density (heavy for their size)-malleable (i.e. it can be hammered)-ductile (drawn into wires). The type of cutting tool used is TNMG tool because as machining material taken is very hard the tool which cuts the material must be much harder. The control factors considered for experiments are spindle speed, feed and depth of cut while cutting force in X direction and temperature are taken as the output responses. The ranges of the process control variables are given in table 1.

Table 1. Ranges of Control variables

Factor	Lower limit	Higher limit
Speed (rpm)	600	1200
Feed (mm/rev)	0.1	0.3
Depth of cut (mm)	0.5	0.9

The experiments were planned using Design of Experiments. The optimal method is one of the experimental designs in the response surface methodology, which optimizes the experimentation volume by reducing the experiments which are out of the control limits and gives only the combination with in the control limits. This list called the design matrix, gives the list of experiments to be performed with the various combinations of the inputs i.e. speed, feed and depth of cut. While performing the turning operation, the final temperatures of the jobs during cutting were taken using laser gun and forces were noted using the dynamo meter. The resultant force and the temperatures were tabulated and the values are as follows.

Table 2. Inputs and outputs table

S.No.	Spindle Speed (RPM)	Feed (mm/rev)	Depth Of Cut (mm)	F_x (Kg-f)	Temperature (^{0}C)
1	1200	0.1	0.9	12	29.2
2	550	0.1	0.5	5	28.4
3	910	0.2	0.9	6	28.8
4	1200	0.15	0.7	13	28.3
5	910	0.1	0.7	6	29.8
6	1200	0.1	0.5	3	29
7	550	0.3	0.9	12	29.2
8	550	0.1	0.5	4	28
9	550	0.1	0.5	4	28.9
10	910	0.2	0.7	7	29.2
11	910	0.1	0.5	2	28
12	550	0.2	0.7	7	28.5
13	550	0.2	0.7	10	28
14	1200	0.3	0.9	16	31
15	1200	0.3	0.9	16	32
16	1200	0.1	0.5	4	30
17	550	0.3	0.9	17	30.1
18	1200	0.1	0.5	7	28
19	910	0.1	0.5	5	28.9
20	910	0.3	0.9	16	29.7
21	910	0.3	0.9	6	29
22	550	0.3	0.9	6	28.9
23	910	0.2	0.7	6	29.3
24	910	0.3	0.9	17	29.3
25	1200	0.2	0.7	6	30.1
26	550	0.1	0.5	4	28.3
27	1200	0.2	0.7	8	29

These values of the various combinations of the inputs and the outputs are mentioned above. We entered the values into the tables of the optimal design and the further analysis will be continued.

3. Modeling Using ANN

ANN inspired by biological nervous systems and composed of simple elements that are operating in parallel and are as shown in Fig. 4.

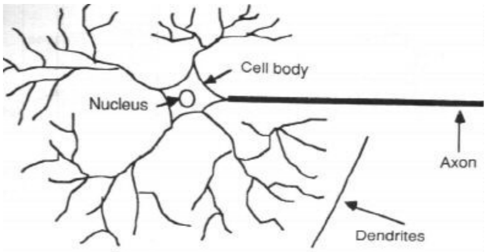

Fig. 4. Biological nervous system

Two different neural network models are used, one for the prediction of MRR and second for the prediction of Tool Wear. Using Levenberg-Marquardt algorithm networks are trained and it is high accurate in similar function approximation [6]. In order to improve the generalization of the network, a 'regularization' scheme was used in conjunction with the Levenberg-Marquardt algorithm. And the automatic Bayesian regularization was used. For training with Levenberg-Marquardt combined with Bayesian regularization, the input/output dataset was divided randomly into two categories: training dataset and test dataset. The first step in ANN modeling is train the network and second step test the network with data, which were not used for training. For mapping the complex and highly inter-active process parameters such as Feed, Depth of Cut & Cutting speed in this paper Back propagation network is used as a tool. For ANN modeling, the Input data, Testing Data set & Target Data set used are taken from the experimental data set developed as per DOE.

ANN model design for prediction of Fx and Temperature.

The model design for F_x & Temperature consists of the following steps. 1) Fixing the number of nodes in output and input layers 2) Normalization of Input and Output 3) Fixing the number of hidden layers and 4) Fixing the number of nodes in each hidden layer. Generally, the nodes of input is equal to number of inputs i.e., in this case it is three.. Similarly the number of output nodes are always equal to number of outputs i.e., one in this case. If the Input and Output values come within the range 0 and 1, then the network performance is considered good. Single and double hidden layers networks are used for solving the problems. This paper used and verified the single layer and is given the maximum error than the single hidden layer. The number of hidden layer nodes can be fixed based on the minimum error. In this case the error is minimum at 8 nodes in first hidden layer and 4 nodes in second hidden layer .

Network model for Fx

The network developed for Fx is based on feed forward back propagation and is trained using Levenberg Maquardtl algorithm. For this Number of layers are taken as 2, and output layer as 1. The number of neurons is taken in between 0 to10. Various others are kept as Training function is TRAINLM, Tran Sigmoid as the hidden layer transfer function and the output layer transfer function as the Pure linear. The adaption of learning rate set as LEARNGDM. The results show that at 52 epochs best regression plot is obtained. Based on the minimum error, the hidden layer node number is fixed. In this case, at 10 Nodes, the error is minimum in first hidden layer and at 3 nodes in second hidden layer and is given in Table 3.

Table 3. Best performance error with hidden nodes for Fx

Hidden Layer	Best performance error
3	0.014
5	0.096
10	0.0019
15	0.032
20	0.064

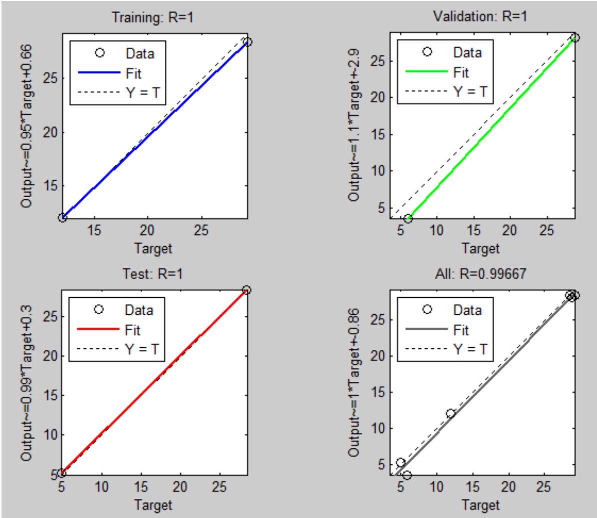

Fig. 5: Best Fx Regression plot

Network model for Temperature

The network developed for temperature is based on feed forward back propagation and is trained using Levenberg Maquardtl algorithm. For this Number of layers are taken as 3, and output layer as 1. The number of neurons is taken in between 0 to 20. Various others are kept as Training function is TRAINLM, Tran Sigmoid as the hidden layer transfer function and the output layer transfer function as the Pure linear. The adaption of learning rate set as LEARNGDM. The results show that at 84 epochs best regression plot is obtained. To obtain best performance i.e with minimum error, the hidden layer nodes are changed. For this the best performance error is less at nodes 17and the 18 and is given in Table4.

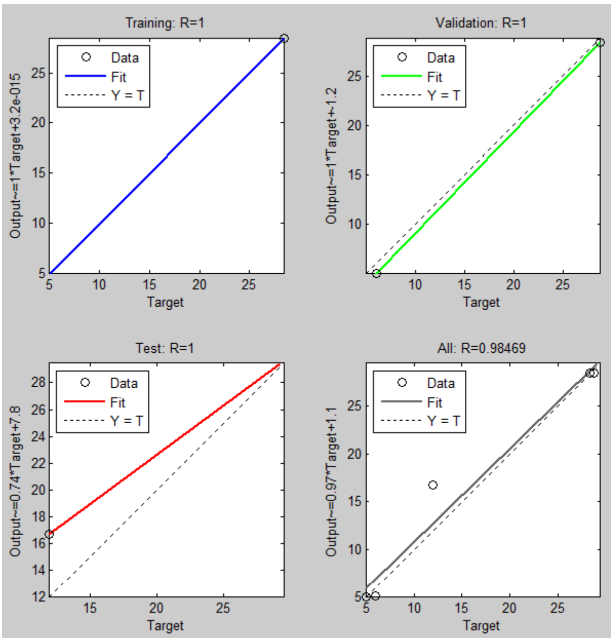

Fig. 6: Best Regression plot for Temperature

Table 4. Best performance error with hidden nodes for Temperature

Hidden Layer	Best performance error
16	0.0276
17	0.0132
18	0.0048
19	0.077
20	0.0989

The predicted values and experimental values of material removal rate and tool were resistance for both training and testing are given in table 5. From that it is evident that network responded well for the testing data as well.

Table 5. Measured and ANN predicted values of Fx and Temperature

S.NO	F_x (Kg-f)		Error %	Temperature (^{0}C)		Error %
	Experimental	ANN Predicted		Experimental	ANN Predicted	
1	12	12.23	0.23	29.2	29.82	0.62
2	5	5.89	0.89	28.4	28.9	0.5
3	6	6.21	0.21	28.8	29	0.2
4	13	13.54	0.54	28.3	28.52	0.22
5	3	3.58	0.58	29	29.52	0.52
6	6	5.62	0.38	29.8	30.10	0.3
7	12	12.21	0.21	29.2	29.9	0.7
8	4	4.62	0.62	28	28.64	0.64
9	4	4.48	0.48	28.9	28.5	-0.4
10	7	7.39	0.39	29.2	29.8	0.6
11	2	2.80	0.80	28	28.65	0.65
12	7	6.92	-0.08	28.5	29	0.5
13	10	10.61	0.61	28	28.8	0.8
14	16	16.82	0.82	31	31.32	0.32
15	16	16.52	0.52	32	31.82	-0.18
16	4	4.30	0.30	30	30.62	0.62
17	17	16.30	-0.199	30.1	30	-0.1
18	7	7.28	0.28	28	28.62	0.62
19	5	5.29	0.29	28.9	28.4	-0.5
20	16	16.29	0.29	29.7	30	0.3
21	6	5.9	-0.1	29	29.32	0.32
22	6	6.29	0.29	28.9	28.5	-0.4
23	6	6.8	0.8	29.3	29.6	0.3
24	17	17.28	0.28	29.3	29.7	0.4
25	6	6.23	0.23	30.1	30.6	0.5
26	4	4.23	0.23	28.3	28.9	0.6
27	8	8.29	0.29	29	29.2	0.2

CONCLUSIONS

In this paper for doing research, All geared lathe is used for doing experiments, employing a variable continuously spindle speed up to a maximum of 1200rpm and maximum spindle power of 5kW. The feed rates is set to a maximum of 0.3 mm/rev. Experiments are done as per DOE. Depth of cut, Cutting speed and Feed is taken as process parameters and the output responses are Fx and Temperature. In Matlab software, ANN module is available which is used to predict the relationships of input process parameters and the output variables. The models were developed to predict the MRR and Tool wear resistance through ANN. For different network configurations, As per the value of performance error obtained, best model is identified and selected. The models are evaluated by calculating the percentage deviation using predicted values and actual values. It is shown that the ANN predicted results show good agreement with the Experimental results, Hence ANN proved its efficiency in optimizing the turning process. The current study optimizes the force and Temperature which are the outputs in the turning process of lathe by adjusting the speed, feed, and depth of cut which are the influencing parameters in the turning process by applying ANN methodology for the EN31. It is found that the speed and the depth of cut have great significance on the force and Temperature, whereas the feed has less significance on both the outputs. The best model is selected based on the best performance error for different network configurations. Also the models have been evaluated by means of the percentage deviation between the predicted values and the actual values. The developed ANN model can be further integrated with optimization algorithms like GA to optimize the turning parameters.

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